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Significant of Blood Glucose Time-Series Forecasting with Temporal Fusion Transformer Model for Type 1 Diabetes

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ABSTRACT

Blood glucose (BG) prediction has advanced to a state of the art thanks to deep learning models, which have been demonstrated to enhance type 1 diabetes (T1D) therapy. Nevertheless, most current models are limited to single-horizon prediction and have several practical drawbacks, including poor interpretability. In this study, we develop a novel approach to optimize the forecasting model in the training processes using the Optuna function, cross-validation, and the latest dataset. We offer a novel deep learning framework for multi-horizon BG prediction: the temporal fusion transformer (TFT). TFT employs a self-attention mechanism to extract long-term temporal dependencies and enables a model with an auto-tuning adjustment approach on hyperparameters and a cross-validation function on univariate and multivariate input models. On a clinical dataset with T1D subjects, namely ShanghaiT1DM (16 subjects), D1NAMO (9 subjects), and OhioT1DM (6 subjects) datasets, it achieved an average root mean square error (RMSE) of the three datasets used. The TFT model gave a lower error score than the baseline models of neural hierarchical interpolation for time series (N-HiTS) and long short-term memory (LSTM) with the values of 10.08±0.31 mg/dL and 12.34±0.62 mg/dL on the univariate input model and 9.18±1.21 mg/dL and 14.33±0.52 mg/dL on the multivariate input model for the prediction horizons of 30 and 60 minutes, respectively. This result explained that the TFT model was adequate for carrying out multi-horizon BG value-level forecasting and potentially deploying on-edge devices to improve clinical efforts to manage BG levels for T1D patients in real-time application.

Keywords:
Temporal Fusion Transformer (TFT); blood glucose forecasting; Type 1 Diabetes (T1D); ShanghaiT1DM; D1NAMO; OhioT1DM; long short-term memory (LSTM); neural hierarchical interpolation for time series (N-HiTS)

1. Introduction

The impact of diabetes has surpassed 500 million people and represents a significant global health challenge while also placing economic strain on numerous nations [1]. As of present, there is no known cure for diabetes, specifically in Type 1 Diabetes (T1D) patients who are unable to naturally produce insulin due to the immune system destruction of insulin-producing cells in the pancreas.

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Hence, individuals with T1D require external insulin, and it is crucial to achieve consistent, enduring management of blood glucose (BG) levels[2]. People facing unregulated BG levels due to diabetes face risks of both increased (hyperglycemia) or decreased (hypoglycemia) levels. Short-term and long-term complications arising from these fluctuations, such as kidney disease, eye disease, and heart problems, might be alleviated by taking proactive steps involving forecasting methods to maintain steady and continuous control over their BG levels [3]. Effectively achieving consistent management of BG levels requires accurate control[4]. Precise forecasting of BG levels using patient time series data for T1D patients is a valuable asset that facilitates proactive interventions and timely administration of medications to enhance the management of T1D patients.

In recent decades, researchers have widely embraced Continuous Glucose Monitoring (CGM), specifically in managing T1D by assessing the concentration of BG values every 5 to 15 minutes and derive essential data to generate precise BG forecasting. The progress in artificial intelligence, particularly in deep learning technology, exhibits impressive performance in establishing BG-level management systems for T1D patients via BG-level forecasting[5],[6],[7]. The application of BG value forecasting using Deep Neural Network (DNN) has been deployed. It has shown superior forecasting outcomes compared to traditional machine learning algorithms like support vector regression (SVR)[8]. Many researchers have specifically extracted temporal characteristics from input sequences by utilizing hidden states[9], drawing from recurrent neural networks (RNNs)[10], which encompass long short-term memory (LSTM)[11],[12], and gated recurrent units (GRUs) [13]. In addition to the progress of systems utilizing attention mechanisms, it has spurred the creation of transformer-based models in time series forecasting applications, exemplified by Informer [14] and Autoformer[15]. Moreover, research has shown that models such as neural hierarchical interpolation for time series (N-HiTS) forecasting exhibit superior performance, mainly when dealing with limited data[16].

Recently, transformer-based DNN models have emerged in time series forecasting, exemplified by the temporal fusion transformer (TFT), a multi-layered transformer equipped with specialized gating mechanisms catering to various real-time data. The engineers precisely designed the TFT to analyze and forecast patterns in time series data. This architecture effectively manages intricate temporal dependencies among data points within a time series. A key benefit of TFT is its utilization of the Self-Attention Mechanism, which enables the model to grasp strong representations of temporal patterns inherent in time series data. This technique lets TFT discern essential relationships and patterns among data points within specific time frames, regardless of specific temporal distances. Therefore, TFT can explicitly use multi-horizon time series forecasting to predict accurately over varying time intervals[17].

Additionally, TFT gains an advantage from its capability to integrate external factors or supplementary variables that impact time series data. By assimilating such contextual details, the model can learn and utilize extra information to improve its forecasting accuracy. Additionally, TFT's primary strength resides in its adaptability and flexibility. Engineered to accommodate diverse time series data, this model's capacity to grasp intricate patterns enables more precise forecasting. Combining these features positions TFT as a resilient model for handling highly complex forecasting tasks in time series data[17].

In this work, by leveraging TFT with its inherent strengths, we propose a TFT model and develop a novel approach to optimize the forecasting model in the training processes using the Optuna function for auto-tuning hyperparameter values and using the latest dataset. It was applied to derive univariate and multivariate input models for the blood glucose time-series forecasting under varying conditions across three distinct T1DM datasets, employing specific approaches. To prevent hypoglycemic and hyperglycemic occurrences based on better accusation of forecasting value from the time series model, transformer-based algorithm, namely TFT as the proposed model, while the multilayer perceptron (MLP)-based N-HiTS and RNN-based LSTM as the baseline models. The models were utilized to forecast future BG values at the 30 and 60-minute prediction horizons (PHs) from the recording data value of time series data. The selection of these PH settings was motivated by the body's insulin absorption rate, and carbohydrates aligning with clinical thresholds that aid in proactive interventions[18],[19],[20] and facilitating comparison with commonly used model outcomes[21],[22],[23]. The following sections organize the remainder of this paper. Section 2 elucidates the framework and specific approaches of the proposed and baseline models and their processes. Section 3 deliberates on the experiments, results of the training processes conducted, and error score to evaluate the performance of the proposed and baseline models. Finally, Section 4 presents the research conclusions and recommendations for future studies to Implement the best model on a high-performance edge device to boost computation speed [24], and explore wearable possibilities.

2. Methodology

This study introduces a deep learning approach for BG forecasting utilizing the Temporal Fusion Transformer (TFT) model for analysis with univariate and multivariate input. Historical BG values from CGM readings (in mg/dl), carbohydrate and insulin intakes as observed input data, with known input data were the timestamps, performance of the multivariate input model is slightly superior because it has other variables as additional features for the support accuracy of the target variable[25]. In the univariate input model, we only considered the observed input data consisting of CGM readings and known input data as the timestamps, while the univariate input models have the advantage that they eliminate the need for manual input[26]. The CGM was the target variable between univariate and multivariate input models during the training phaseput model.

The three datasets used in this research are not in silico data generated through simulation but clinical data collected from real-life conditions, namely ShanghaiT1DM (16 subjects)[27], D1NAMO (9 subjects)[28], and OhioT1DM (6 subjects) datasets[29]. The study employs an approach to determining optimal hyperparameter values via auto-tuning functions. Figure 1 visually represents the comprehensive workflow of this research. The study adopts multiple procedural steps, encompassing data configuration based on the three T1D datasets, the BG time-series data trains the three models, and a time-series cross-validation technique optimizes the hyperparameters for 30 and 60-minute prediction horizons (PHs) [30][31][32][33], and evaluation of the model performance.

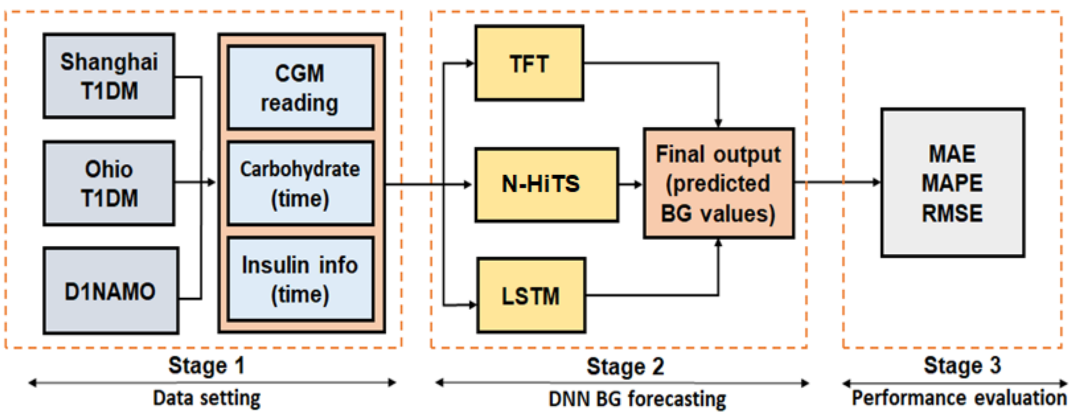


Fig. 1. Block diagram of the BG prediction framework

In this study, we utilized three models with a consistent approach: TFT as the proposed model, N-HiTS, and LSTM as baseline models to compare the performance of the proposed model. N-HiTS is a cutting-edge model with an MLP-based deep neural architecture that addresses challenges in time series forecasting by incorporating innovative hierarchical interpolation and multi-rate data sampling techniques[34]. This model has been recognized as one of the state-of-the-art base point forecasters alongside TFT[35]. The advantage of N-HiTS lies in its ability to provide accurate forecasts by leveraging hierarchical interpolation methods, which enable it to effectively handle complex time series data structures and varying sampling rates[34]. LSTM, an architecture of DNN based on Recurrent Neural Network (RNN), learns discrete-time steps by maintaining constant error flow in specific units and controlling gradient impact. It demonstrates spatial-temporal locality and computational complexity per time step. LSTM utilizes diverse pattern representations in the simulated data research, outperforming various recurrent network speeds and effectiveness, particularly in handling tasks with prolonged time lags[12][36].

2.1 Stage 1: Data Setting

The study utilized three distinct datasets made available online for research aims to support the development of deep learning models. These models used only the CGM readings as input for the univariate input model. Additionally, we transformed carbohydrate and insulin information Into binary values (0 and 1) to serve as supplementary variables in the multivariate input model for forecasting the BG time series[25]. The data were organized and indexed according to date and time using the Python datetime function.

The T1D datasets used in this study originated from three distinct sources. Dataset 1, originating from ShanghaiT1DM, is publicly accessible for research purposes and contains data from 12 adult patients diagnosed with T1D. We collected these data under real-life conditions, including CGM readings and information on carbohydrates and insulin, spanning 3 to 14 days. Measurements were taken at 15-minute intervals[27],[37]. Dataset 2, extracted from the OhioT1DM dataset released in 2020, encompasses information from individuals diagnosed with T1D. This study utilized the most recent dataset, gathered by monitoring six patients at 5-minute intervals. The dataset comprises CGM readings, carbohydrate and insulin intake details, and documented life events consistently collected over eight weeks[29]. Dataset 3, sourced from D1NAMO, includes individual health indicators and activity levels among individuals with T1D. This dataset comprises accelerometer data, electrocardiogram (ECG) readings, respiration data, CGM readings, and information on carbohydrates and insulin. The measurements were obtained by monitoring nine patients at 5-minute intervals over four days[28][38].

All datasets have missing values in the CGM measurements due to several plausible reasons, such as signal loss and sensor calibration. Proper pre-processing to extract appropriate T1D patient data and characteristics is essential involving using a sensor operating range of 40–400 mg/dL to handle the missing values with clipping values and applying linear extrapolation [39],[40]. We split each dataset into 80% for training and 20% for testing. We used the final 25% from each training set to create a validation set. This two-step data split is common in machine learning-based BG prediction research[6][41][42][43].

2.2 Stage 2: DNN BG forecasting models

This study proposes the architectural design of the TFT model as the primary model for forecasting BG values. Mean Absolute Error (MAE) is the loss function for the proposed model architecture during the training process. We produced the input data and the corresponding target values used by the model; TFT provides powerful exponential linear unit (ELU) activation to reduce the impact of outliers or noise on input time series data. After feeding the data into the TFT model, the parameters are automatically updated through back-propagation using the Adam optimizer. We use 200 training epochs with a patience level of 20 to reduce overfitting and provide an early stopping mechanism[26].

Meanwhile, configuring hyperparameters is crucial to attain better forecasting performance before model training. Determining the optimal hyperparameter values for the proposed model involves adjusting several combinations of commonly used primary hyperparameter values. These values significantly influence the model training, serving as an initial step in model learning. Inappropriate hyperparameter values could hinder effective model learning.

Moreover, the baseline models N-HiTS and LSTM were developed similarly to the primary model. Later, we will compare these models and conclude by ascertaining which model performs best in forecasting BG values based on three model performance metrics described in section 2.3 for each PHs of 30 and 60 minutes, respectively. We developed the forecasting models using Python 3.10.10, PyTorch 2.0.1, and Nvidia GeForce GTX 1650 SUPER as the GPU computational device. The GPU technology will be highly beneficial as models with many parameters require extensive computation time[44].

2.2.1 Auto-tuning function

Automatic tuning functions were employed across all models to attain the optimal hyperparameter values. The Optuna auto-tuning function was used to automatically get the best hyperparameter values. This auto-tuning function is a search algorithm from the Ray tune library[45], designed for hyperparameter optimization. Optuna offers advantages in automating hyperparameter tuning, optimizing complex hyperparameter spaces, and supporting various optimization algorithms[46]. By leveraging Optuna in time series modeling, researchers can enhance the accuracy and efficiency of forecasting models[47]. This automation saves time and effort compared to manual tuning, allowing for a more systematic and comprehensive exploration of hyperparameter configurations[48]. Manual selection of model hyperparameter values can be time-consuming, especially when considering multiple hyperparameter combinations.

Furthermore, it is more accurate because the auto-tuning process explores numerous hyperparameter combinations. The manual method involves trial and error in selecting hyperparameter values, usually testing only a few commonly used combinations[49],[50]. Table 1 presents the main hyperparameter value combinations used in this study[51],[52].

Table 1.
Combination of hyperparameter values

Main hyperparameter types	Combination values
"n_head"	: tune.choice([4, 8]), # Number of multi head attention
"hidden_size"	: tune.choice([64, 128, 256]), # Size of embeddings and encoders
"learning_rate"	: tune.loguniform(1e-4, 1e-2, 1e-1), # Initial learning rate
"max_steps"	: tune.choice([200, 500, 1000]), # Max number of training iterations
"batch_size"	: tune.choice([32, 64, 128]), # Number of series in batch
"windows_batch_size"	: tune.choice([128, 256, 512]), # Number of windows in batch
"random_seed"	: tune.randint(1, 20), # Random seed
"scaler_type"	: tune. choice([‘robust’, ‘standard’] # Type of scaler

2.2.2 Cross-Validation with Chained Windows

In this study, developing deep learning models involved training the model with each dataset utilized and employing the best-obtained hyperparameter values for BG forecasting, incorporating time series cross-validation as part of the training process. The cross-validation applied in this study is a method where the data is partitioned into several windows, conducting chained windows cross-validation in each window by expanding and transitioning the data for time series model training and validation. This ensures the model performance with new sequence data. The chained windows cross-validation was adopted from the NeuralForecast library and previous work[50] [51].

Each window was the final 25% from each training set for the validation set and 20% for testing to evaluate each model's performance. The outcome of the chained windows cross-validation is the forecasting value within each window. Using evaluation metrics, we use this forecasting value to assess the overall model performance. The most common metrics error scores in BG prediction are the RMSE and MAE[5] and the MAPE, a percentage metric that offers insights into relative prediction errors[26].

2.3 Stage 3: Performance Evaluation

Stage 3 delineates the approach for assessing the model performance based on BG forecasting values obtained from the cross-validation process that conducted training while simultaneously displaying forecasting results to compare with actual BG values using evaluation metrics. We assessed the model performance based on the three datasets. We evaluated the deep learning model performance using the test data for each dataset source, employing MAE, MAPE, and RMSE to calculate based on equations (1), (2), and (3), respectively.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|a_i - b_i| \tag{1}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{|a_i - b_i|}{a_i} * 100\% \tag{2}$$

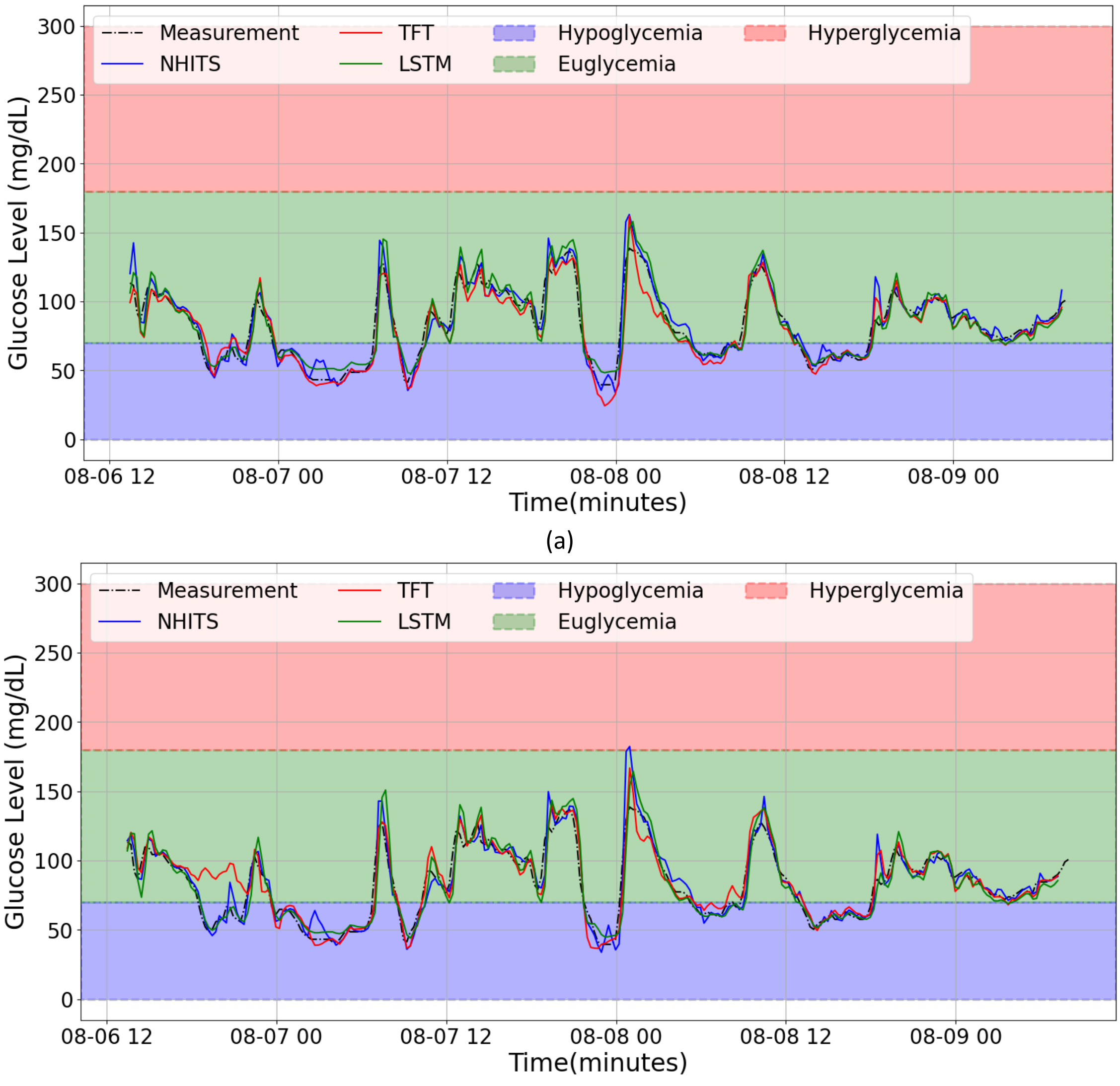
$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(a_i - b_i\ )^2}{n}} \tag{3}$$

In this study, the variables are defined as follows: n represents the amount of data in the variables a_i (actual value) and b_i (predicted value). Here, a_i denotes the actual data value at the i-th observation and b_i indicates the predicted data value at the i -th observation. The index i is the value index of each observation.

3. Results and discussion

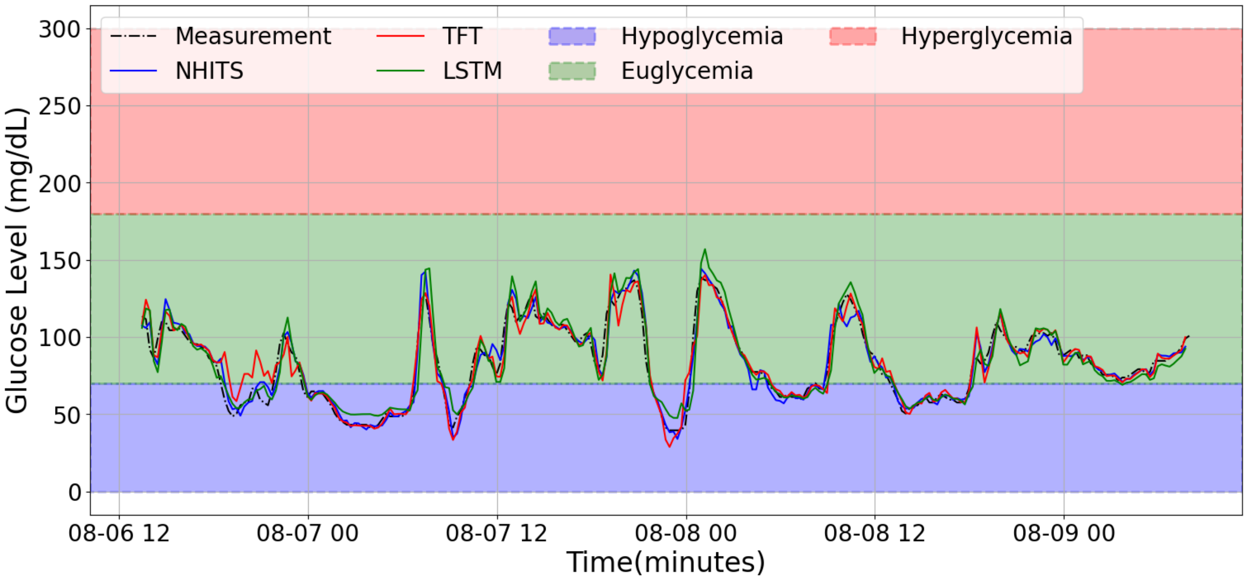
This section bases its content on the BG time series forecasting conducted with the proposed TFT model trained and tested with univariate input of the CGM readings only and with multivariate inputs of the CGM readings**,** carbohydrate, and insulin takes from the ShanghaiT1D, D1NAMO, and OhioT1DM datasets. These models forecasted BG values based on 30 and 60-minute PHs. The forecasting results from the proposed TFT model were also compared with baseline models (N-HiTS and LSTM). However, due to space limitations, the comparative graphs presented in this paper are only from the Shanghai dataset with a T1D individual in the ShanghaiT1DM dataset. Figure 2 and Figure 3, respectively show the comparison graphs of the BG time-series data between the actual (measurement) data from the test data and its prediction data from the univariate input and multivariate input models. There are three zones of blood glucose levels: hypoglycemia, euglycemia, and hyperglycemia. Hypoglycemia occurs when blood glucose levels drop below 70 mg/dL. Euglycemia refers to normal blood glucose levels ranging from 70 to 100 mg/dL when fasting and remaining below 140 mg/dL after eating. Meanwhile, hyperglycemia occurs when blood glucose levels are above normal, with fasting levels exceeding 126 mg/dL and postprandial levels above 180 mg/dL[53][54].

Due to the limited space, the comparison graphs in this paper are only from the ShanghaiT1DM dataset with record numbers of 11A with univariate and multivariate input models, respectively. Upon observing the graphs and comparing the actual and forecasted data, the proposed TFT model demonstrated relative superiority to N-HiTS and LSTM. Furthermore, within the proposed TFT model, at the 30-minute PHs, the graphs indicate that actual BG values and forecasted values are closer than at the 60-minute PHs.

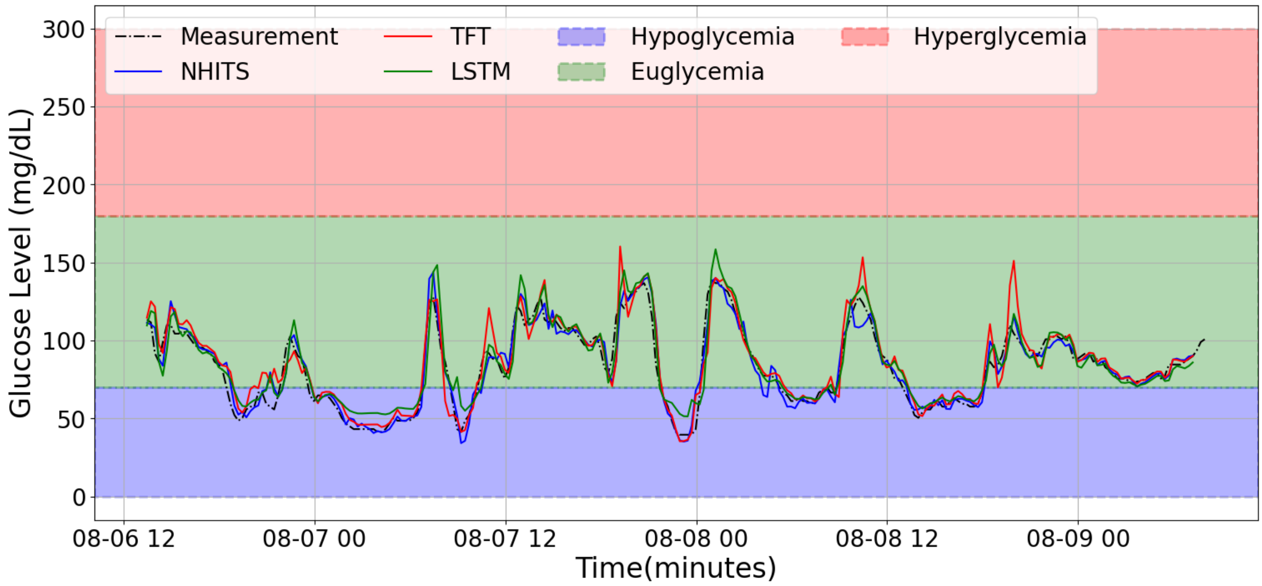


(b)

Fig. 2. A T1D individual in the ShanghaiT1DM dataset on univariate input models
(a) PH=30 minutes) (b) PH=60 minutes



(a)



(b)

Fig. 3. A T1D individual in the ShanghaiT1DM dataset on multivariate input models
(a) PH=30 minutes) (b) PH=60 minutes

The performance assessment outcomes of the three models, the TFT, N-HiTS, and LSTM, both univariate and multivariate input models, are detailed in Table 2 using performance metrics of MAE, MAPE, and RMSE. These metrics illustrate the outcomes derived from the average error scores across the three testing datasets, with the bold values indicating the best score among the three models in each performance metric.

The results further suggest that the proposed TFT model significantly outperformed the LSTM baseline model and the N-HiTS baseline model, with a relatively higher difference between the proposed TFT model and each baseline model. Notably, the baseline model error scores exhibit considerably larger average error scores compared to the proposed model.

Table 2
Average Error Scores for time-series univariate and multivariate input models from the three T1D datasets

Univariate input model						
	PH = 30 min			**PH = 60 min**		
Models	**MAE (mg/dl)**	**MAPE (%)**	**RMSE (mg/dl)**	**MAE (mg/dl)**	**MAPE (%)**	**RMSE (mg/dl)**
TFT	8.20 ±1.23	11.47 ±1.56	10.08 ±0.31	12.49 ±1.65	22.53 ±2.64	12.34+0.62
N-HiTS	9.28 ±3.53	12.10 ±1.68	11.18 ±1.21	13.49 ±2.68	23.89 ±3.56	15.13 ±1.86
LSTM	13.54 ±1.41	11.92 ±1.5	18.42 ±1.16	16.59 ±3.68	15.42 ±1.98	21.12 ±1.14
Multivariate input model						
	PH = 30 min			**PH = 60 min**		
Models	**MAE (mg/dl)**	**MAPE (%)**	**RMSE (mg/dl)**	**MAE (mg/dl)**	**MAPE (%)**	**RMSE (mg/dl)**
TFT	6.50 ±2.64	8.04 ±3.63	9.18 ±1.21	10.87 ±0.53	13.31 ±2.5	14.33 ±0.52
N-HiTS	10.84 ±2.35	10.17 ±1.34	11.14 ±1.12	12.21 ±1.24	15.13 ±1.16	16.26 ±2.36
LSTM	12.24 ±1.64	14.38 ±2.51	15.05 ±1.32	14.53 ±1.32	18.40 ±2.8	18.23 ±1.14

In comparing forecasting results between univariate and multivariate input models, observations from Table 2 indicate that the error scores of the multivariate input model are better than those of the univariate input model. This performance improvement is attributed to including carbohydrate and insulin information as additional features in the multivariate input model, providing valuable insights throughout the training process. Additionally, when considering the forecasting outcomes between the 30-minute and 60-minute PHs values, the errors associated with the 30-minute PHs are comparatively smaller than those associated with the 60-minute PHs.

The more significant error score in the 60-minute PHs might stem from the dynamic nature of the BG time-series data, making the BG values more intricate to forecast over longer PHs. Additionally, there exists a trade-off between computational time and the performance of the forecasting system when determining the length of PHs, as lower PHs demand less computational time.

4. Conclusion

The TFT model, a novel high-performance forecasting model, is introduced in this study as the proposed model. Two baseline models, namely N-HiTS and LSTM, were also employed. Specifically, we applied the same auto-tuning approach for hyperparameters and cross-validation using chained windows to the proposed TFT and baseline models during the model training process. Employing three clinical dataset sources with T1D subjects, namely the ShanghaiT1DM (16 subjects), D1NAMO (9 subjects), and OhioT1DM (6 subjects) datasets, the TFT model, utilizing the provided approach, demonstrated a better average root mean square error (RMSE) from the three dataset sources compared to the baseline models. The TFT model outperformed the baseline models with values of 10.08 ±0.31 mg/dL and 12.34 ±0.62 mg/dL, compared to the baseline N-HiTS model values of 12.18 ±1.21 mg/dL and 15.13 ±1.86 mg/dL and LSTM values of 18.42 ±1.16 mg/dL and 21.12 ±1.14 mg/dL for the univariate input model. TFT increasing performance 9.18 ±1.21 mg/dL and 14.33 ±0.52 mg/dL, compared to the baseline N-HiTS model values of 11.14 ±1.12 mg/dL and 16.26 ±2.36 mg/dL and LSTM values of 15.05 ±1.32 mg/dL and 18.23 ±1.14 mg/dL for the multivariate input model forecasting periods of PHs 30 and 60 minutes, respectively. The proposed model showcased better performance than the baseline models, especially on the multivariate input model, validating the effectiveness of the approach employed to derive optimal hyperparameter values and the cross-validation function as a training method for the model. The TFT model was effective for multi-horizon blood glucose value forecasting and could be deployed on edge devices to improve real-time clinical management of BG levels in T1D patients. For future research, the best model will be implemented on a high-performance edge device, such as a mini-computer with advanced GPU capabilities, to enhance computation speed and explore wearable device possibilities.

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References

[1] Sun, Hong, Pouya Saeedi, Suvi Karuranga, Moritz Pinkepank, Katherine Ogurtsova, Bruce B. Duncan, Caroline Stein et al. "IDF Diabetes Atlas: Global, regional and country-level diabetes prevalence estimates for 2021 and projections for 2045." *Diabetes research and clinical practice* 183 (2022): 109119. https://doi.org/109119.10.1016/j.diabres.2021.109119

[2] Tauschmann, Martin, and Roman Hovorka. "Technology in the management of type 1 diabetes mellitus—current status and future prospects." *Nature Reviews Endocrinology* 14, no. 8 (2018): 464-475. https://doi.org/10.1038/s41574-018-0044-y

[3] Riordan, Barrett. "The mathematics of O'Brien's principle: an invitation to quantification." *Intelligence and National Security* 18, no. 3 (2003): 168-173. https://doi.org/10.1080/02684520412331306970

[4] Zhu, Taiyu, Kezhi Li, Jianwei Chen, Pau Herrero, and Pantelis Georgiou. "Dilated recurrent neural networks for glucose forecasting in type 1 diabetes." *Journal of Healthcare Informatics Research* 4 (2020): 308-324. https://doi.org/10.1007/s41666-020-00068-2

[5] Zhu, Taiyu, Kezhi Li, Pau Herrero, and Pantelis Georgiou. "Deep learning for diabetes: a systematic review." *IEEE Journal of Biomedical and Health Informatics* 25, no. 7 (2020): 2744-2757. https://doi.org/10.1109/JBHI.2020.3040225

[6] Zhu, Taiyu, Kezhi Li, Pau Herrero, and Pantelis Georgiou. "Personalized blood glucose prediction for type 1 diabetes using evidential deep learning and meta-learning." *IEEE Transactions on Biomedical Engineering* 70, no. 1 (2022): 193-204. https://doi.org/10.1109/TBME.2022.3187703

[7] Zhu, Taiyu, Kezhi Li, Lei Kuang, Pau Herrero, and Pantelis Georgiou. "An insulin bolus advisor for type 1 diabetes using deep reinforcement learning." *Sensors* 20, no. 18 (2020): 5058. https://doi.org/10.3390/s20185058

[8] Georga, Eleni I., Vasilios C. Protopappas, Diego Ardigo, Michela Marina, Ivana Zavaroni, Demosthenes Polyzos, and Dimitrios I. Fotiadis. "Multivariate prediction of subcutaneous glucose concentration in type 1 diabetes patients based on support vector regression." *IEEE journal of biomedical and health informatics* 17, no. 1 (2012): 71-81. https://doi.org/10.1109/TITB.2012.2219876

[9] Talha, Ahmed Zakaria, Noureldin S. Eissa, and Mohd Ibrahim Shapiai. "Applications of Brain Computer Interface for Motor Imagery Using Deep Learning: Review on Recent Trends." *Journal of Advanced Research in Applied Sciences and Engineering Technology* 40, no. 2 (2024): 96-116. https://doi.org/10.37934/araset.40.2.96116

[10] Rabby, Md Fazle, Yazhou Tu, Md Imran Hossen, Insup Lee, Anthony S. Maida, and Xiali Hei. "Stacked LSTM based deep recurrent neural network with kalman smoothing for blood glucose prediction." *BMC Medical Informatics and Decision Making* 21 (2021): 1-15. https://doi.org/10.1186/s12911-021-01462-5

[11] Kalita, Deepjyoti, and Khalid B. Mirza. "Glucose prediction using wide-deep lstm network for accurate insulin dosing in artificial pancreas." In *2022 44th Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*, pp. 4426-4429. IEEE, 2022. https://doi.org/10.1109/EMBC48229.2022.9870983

[12] Alex, Suja A., N. Z. Jhanjhi, Mamoona Humayun, Ashraf Osman Ibrahim, and Anas W. Abulfaraj. "Deep LSTM model for diabetes prediction with class balancing by SMOTE." *Electronics* 11, no. 17 (2022): 2737. https://doi.org/10.3390/electronics11172737

[13] Wang, Donghun, Jihwan Hwang, Jonghyun Lee, Minchan Kim, and Insoo Lee. "Temperature-Based State-of-Charge Estimation Using Neural Networks, Gradient Boosting Machine and a Jetson Nano Device for Batteries." *Energies* 16, no. 6 (2023): 2639. https://doi.org/10.3390/en16062639

[14] Zhou, Haoyi, Shanghang Zhang, Jieqi Peng, Shuai Zhang, Jianxin Li, Hui Xiong, and Wancai Zhang. "Informer: Beyond efficient transformer for long sequence time-series forecasting." In *Proceedings of the AAAI conference on artificial intelligence*, vol. 35, no. 12, pp. 11106-11115. 2021. [Online]. Available: https://ojs.aaai.org/index.php/AAAI/article/view/17325

[15] Wu, Haixu, Jiehui Xu, Jianmin Wang, and Mingsheng Long. "Autoformer: Decomposition transformers with auto-correlation for long-term series forecasting." *Advances in neural information processing systems* 34 (2021): 22419-

22430. [Online]. Available: https://proceedings.neurips.cc/paper/2021/hash/bcc0d400288793e8bdcd7c19a8ac0c2b-Abstract.html

[16] Maheronnaghsh, Mohammad Javad, Mohammad Mahdi Gheidi, Abolfazl Younesi, and Mohammad Amin Fazli. *Machine Learning Methods in Algorithmic Trading: An Experimental Evaluation of Supervised Learning Techniques for Stock Price*. No. dzp26. Center for Open Science, 2023. https://doi.org/10.31219/osf.io/dzp26

[17] Lim, Bryan, Sercan Ö. Arık, Nicolas Loeff, and Tomas Pfister. "Temporal fusion transformers for interpretable multi-horizon time series forecasting." *International Journal of Forecasting* 37, no. 4 (2021): 1748-1764. https://doi.org/10.1016/j.ijforecast.2021.03.012

[18] Battelino, Tadej, Thomas Danne, Richard M. Bergenstal, Stephanie A. Amiel, Roy Beck, Torben Biester, Emanuele Bosi et al. "Clinical targets for continuous glucose monitoring data interpretation: recommendations from the international consensus on time in range." *Diabetes care* 42, no. 8 (2019): 1593-1603. https://doi.org/10.2337/dci19-0028

[19] Vijayam, Bhuwaneswaran, Lau Siew Ping, Wong Jing Wen, Sakinah Muzarpar, Ainun Amirah Abdul Rahim, Pwi Jia Yee, and Leeynesh Sooriyapiragasam. "Validation of Glycemic Index Values Represented as Bar Graphs in Scholarly Articles for Clinical Nutrition Application." *Journal of Health and Quality of Life* 1, no. 1 (2024): 1-15. https://doi.org/10.37934/jhqol.1.1.115

[20] Kaveripakam, Dhasaradhan, and Jaichandran Ravichandran. "Comparative Analysis of Machine Learning Algorithms for Diabetic Disease Identification." *Journal of Advanced Research in Applied Sciences and Engineering Technology* 45, no. 1 (2025): 40-50. https://doi.org/10.37934/araset.45.1.4050

[21] Munoz-Organero, Mario. "Deep physiological model for blood glucose prediction in T1DM patients." *Sensors* 20, no. 14 (2020): 3896. https://doi.org/10.3390/s20143896

[22] Li, Kezhi, John Daniels, Chengyuan Liu, Pau Herrero, and Pantelis Georgiou. "Convolutional recurrent neural networks for glucose prediction." *IEEE journal of biomedical and health informatics* 24, no. 2 (2019): 603-613. https://doi.org/10.1109/JBHI.2019.2908488

[23] Deng, Yixiang, Lu Lu, Laura Aponte, Angeliki M. Angelidi, Vera Novak, George Em Karniadakis, and Christos S. Mantzoros. "Deep transfer learning and data augmentation improve glucose levels prediction in type 2 diabetes patients." *NPJ Digital Medicine* 4, no. 1 (2021): 109. https://doi.org/10.1038/s41746-021-00480-x

[24] Ade Anggian Hakim, Elmo Juanara, and Rispandi Rispandi. "Mask Detection System with Computer Vision-Based on CNN and YOLO Method Using Nvidia Jetson Nano." *Journal of Information System Exploration and Research* 1, no. 2 (2023). https://doi.org/10.52465/joiser.v1i2.175

[25] Kim, Dae-Yeon, Dong-Sik Choi, Ah Reum Kang, Jiyoung Woo, Yechan Han, Sung Wan Chun, and Jaeyun Kim. "Intelligent ensemble deep learning system for blood glucose prediction using genetic algorithms." *Complexity* 2022, no. 1 (2022): 7902418. https://doi.org/10.1155/2022/7902418

[26] Zhu, Taiyu, Lei Kuang, Chengzhe Piao, Junming Zeng, Kezhi Li, and Pantelis Georgiou. "Population-specific glucose prediction in diabetes care with transformer-based deep learning on the edge." *IEEE Transactions on Biomedical Circuits and Systems* (2024). https://doi.org/10.1109/TBCAS.2023.3348844

[27] Zhao, Qinpei, Jinhao Zhu, Xuan Shen, Chuwen Lin, Yinjia Zhang, Yuxiang Liang, Baige Cao et al. "Chinese diabetes datasets for data-driven machine learning." *Scientific Data* 10, no. 1 (2023): 35. https://doi.org/10.1038/s41597-023-01940-7

[28] Dubosson, Fabien, Jean-Eudes Ranvier, Stefano Bromuri, Jean-Paul Calbimonte, Juan Ruiz, and Michael Schumacher. "The open D1NAMO dataset: A multi-modal dataset for research on non-invasive type 1 diabetes management." *Informatics in Medicine Unlocked* 13 (2018): 92-100. https://doi.org/10.1016/j.imu.2018.09.003

[29] Marling, Cindy, and Razvan Bunescu. "The OhioT1DM dataset for blood glucose level prediction: Update 2020." In *CEUR workshop proceedings*, vol. 2675, p. 71. NIH Public Access, 2020. [Online]. Available: https://pubmed.ncbi.nlm.nih.gov/33584164/

[30] Tahkola, Mikko, and Zou Guangrong. "Atsc-nex: Automated time series classification with sequential model-based optimization and nested cross-validation." *IEEE Access* 10 (2022): 39299-39312. https://doi.org/10.1109/access.2022.3166525

[31] Matsui, Takanori, Kanoko Suzuki, Kyota Ando, Yuya Kitai, Chihiro Haga, Naoki Masuhara, and Shun Kawakubo. "A natural language processing model for supporting sustainable development goals: translating semantics, visualizing nexus, and connecting stakeholders." *Sustainability Science* 17, no. 3 (2022): 969-985. https://doi.org/10.1007/s11625-022-01093-3

[32] Dong, Hai, Xiuxiu Gao, and Mingqi Wei. "Quality prediction of fused deposition molding parts based on improved deep belief network." *Computational Intelligence and Neuroscience* 2021, no. 1 (2021): 8100371. https://doi.org/10.1155/2021/8100371

[33] Rofik, Rofik, Reza Aulia, Khalimah Musaadah, Salma Shafira Fatya Ardyani, and Ade Anggian Hakim. "The Optimization of Credit Scoring Model Using Stacking Ensemble Learning and Oversampling Techniques." *Journal of Information*

System Exploration and Research 2, no. 1 (2024). https://doi.org/10.52465/joiser.v2i1.203

[34] Challu, Cristian, Kin G. Olivares, Boris N. Oreshkin, Federico Garza Ramirez, Max Mergenthaler Canseco, and Artur Dubrawski. "Nhits: Neural hierarchical interpolation for time series forecasting." In *Proceedings of the AAAI conference on artificial intelligence*, vol. 37, no. 6, pp. 6989-6997. 2023. https://doi.org/10.48550/arxiv.2201.12886

[35] Phipps, Kaleb, Benedikt Heidrich, Marian Turowski, Moritz Wittig, Ralf Mikut, and Veit Hagenmeyer. "Generating probabilistic forecasts from arbitrary point forecasts using a conditional invertible neural network." *Applied Intelligence* (2024): 1-29. https://doi.org/10.1007/s10489-024-05346-9

[36] Hochreiter, Sepp, and Jürgen Schmidhuber. "Long short-term memory." *Neural computation* 9, no. 8 (1997): 1735-1780. https://doi.org/10.1162/neco.1997.9.8.1735

[37] Ade Anggian Hakim, Farhanahani Mahmud, and Marlia Morsin. "Assessment of Deep Learning Model System for Blood Glucose Time-Series Prediction." *Journal of Science and Technology* 16, no. 1 (2024): 65-75. https://doi.org/10.30880/jst.2024.16.01.007

[38] Kumari, Ranjita, Pradeep Kumar Anand, and Jitae Shin. "Improving the Accuracy of Continuous Blood Glucose Measurement Using Personalized Calibration and Machine Learning." *Diagnostics* 13, no. 15 (2023): 2514. https://doi.org/10.3390/diagnostics13152514

[39] Zhu, Taiyu, Tianrui Chen, Lei Kuangt, Junming Zeng, Kezhi Li, and Pantelis Georgiou. "Edge-based temporal fusion transformer for multi-horizon blood glucose prediction." In *2023 IEEE International Symposium on Circuits and Systems (ISCAS)*, pp. 1-5. IEEE, 2023. https://doi.org/10.1109/ISCAS46773.2023.10181448

[40] Roslan, Nurhana, Jastini Mohd Jamil, Izwan Nizal Mohd Shaharanee, and Sultan Juma Sultan Alawi. "Prediction of Student Dropout in Malaysian's Private Higher Education Institute using Data Mining Application." *Journal of Advanced Research in Applied Sciences and Engineering Technology* 45, no. 2 (2025): 168-176. https://doi.org/10.37934/araset.45.2.168176

[41] He, Miao, Weixi Gu, Ying Kong, Lin Zhang, Costas J. Spanos, and Khalid M. Mosalam. "CausalBG: Causal recurrent neural network for the blood glucose inference with IoT platform." *IEEE Internet of Things Journal* 7, no. 1 (2019): 598-610. https://doi.org/10.1109/JIOT.2019.2946693

[42] Zhu, Taiyu, Chukwuma Uduku, Kezhi Li, Pau Herrero, Nick Oliver, and Pantelis Georgiou. "Enhancing self-management in type 1 diabetes with wearables and deep learning." *npj Digital Medicine* 5, no. 1 (2022): 78. https://doi.org/10.1038/s41746-022-00626-5

[43] Mirshekarian, Sadegh, Hui Shen, Razvan Bunescu, and Cindy Marling. "LSTMs and neural attention models for blood glucose prediction: Comparative experiments on real and synthetic data." In *2019 41st annual international conference of the IEEE engineering in medicine and biology society (EMBC)*, pp. 706-712. IEEE, 2019. https://doi.org/10.1109/EMBC.2019.8856940

[44] Mahmud, Farhanahani, Nur Atiqah Adon, Norliza Othman, Ade Anggian Hakim, Marlia Morsin, and Mohamad Hairol Jabbar. "A Reconfigurable Hardware Realization for Real-Time Simulation of Cardiac Excitation and Conduction." *International Journal of Integrated Engineering* 16, no. 1 (2024): 272-281. https://doi.org/10.30880/ijie.2024.16.01.022

[45] "Open Source Time Series Ecosystem (2023, Desember 10). Evaluate the model's performance. Retrieved December 7, 2023, [Online]. Available: https://nixtla.github.io/neuralforecast/models.lstm.html

[46] Elshewey, Ahmed M. "hyOPTGB: An Efficient OPTUNA Hyperparameter Optimization Framework for Hepatitis C Virus (HCV) Disease Prediction in Egypt." (2023). https://doi.org/10.21203/rs.3.rs-2768795/v1

[47] Lai, Jung-Pin, Ying-Lei Lin, Ho-Chuan Lin, Chih-Yuan Shih, Yu-Po Wang, and Ping-Feng Pai. "Tree-based machine learning models with optuna in predicting impedance values for circuit analysis." *Micromachines* 14, no. 2 (2023): 265. https://doi.org/10.3390/mi14020265

[48] Yu, Jiahao, Yongman Zhao, Rongshun Pan, Xue Zhou, and Zikai Wei. "Prediction of the critical temperature of superconductors based on two-layer feature selection and the optuna-stacking ensemble learning model." *ACS omega* 8, no. 3 (2023): 3078-3090. https://doi.org/10.1021/acsomega.2c06324

[49] "Open Source Time Series Ecosystem (2023, December 7). Hyperparameter Optimization. Retrieved December 7, 2023, [Online]. Available: https://nixtlaverse.nixtla.io/neuralforecast/examples/automatic_hyperparameter_tuning.html

[50] Zhang, Fan, Melissa Petersen, Leigh Johnson, James Hall, and Sid E. O'Bryant. "Hyperparameter tuning with high performance computing machine learning for imbalanced Alzheimer's disease data." *Applied Sciences* 12, no. 13 (2022): 6670. https://doi.org/10.3390/app12136670

[51] Zhang, Fan, Melissa Petersen, Leigh Johnson, James Hall, and Sid E. O'Bryant. "Accelerating hyperparameter tuning in machine learning for Alzheimer's disease with high performance computing." *Frontiers in Artificial Intelligence* 4 (2021): 798962. https://doi.org/10.3389/frai.2021.798962

[52] Stefenon, Stefano Frizzo, Laio Oriel Seman, Luiza Scapinello Aquino da Silva, Viviana Cocco Mariani, and Leandro dos Santos Coelho. "Hypertuned temporal fusion transformer for multi-horizon time series forecasting of dam level in hydroelectric power plants." *International Journal of Electrical Power & Energy Systems* 157 (2024): 109876. https://doi.org/10.1016/j.ijepes.2024.109876

[53] Bode, Bruce W., Sherwyn Schwartz, Harrison A. Stubbs, and Jon E. Block. "Glycemic characteristics in continuously monitored patients with type 1 and type 2 diabetes: normative values." *Diabetes care* 28, no. 10 (2005): 2361-2366. https://doi.org/10.2337/diacare.28.10.2361

[54] Oba, Kenzo, Yuki Inuzuka, Naoko Yamashita-Onodera, Kentaro Watanabe, Noriaki Matsumura, Yoshimasa Igari, Tatsuya Suzuki, and Hiroshi Nakano. "Lower occurrence of low blood glucose level in elderly type 2 diabetic patients treated with gliclazide versus glibenclamide." *Geriatrics & gerontology international* 7, no. 1 (2007): 91-93. https://doi.org/10.1111/j.1447-0594.2007.00369.x